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A modular optimisation model for reducing energy consumption in large scale building facilities ☆

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ABSTRACT

With the pressing regulatory requirement to increase energy efficiency in our built environment, significant researching efforts have been recently directed towards energy optimisation with the overall objective of reducing energy consumption. Energy simulation and optimisation identify a class of applications that demand high performance processing power in order to be realised within a feasible time-frame. The problem becomes increasingly complex when undertaking such energy simulation and optimisation in large scale buildings such as sport facilities where the generation of optimal set points can be timing inefficient.

In this paper we present how a modular based optimisation system can be efficiently used for running energy simulation and optimisation in order to fulfil a number of energy related objectives. The solution can address the variability in building dynamics and provide support for building managers in implementing energy efficient optimisation plans. We present the optimisation system that has been implemented based on energy saving specifications from EU FP7 project – *SportE*^{2} (Energy Efficiency for Sport Facilities) and evaluate the efficiency of the system over a number of relevant use-case scenarios.

Contents

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1. Introduction

Recent research has revealed that buildings are significantly contributing to global warming. Energy usage in buildings has grown in the last 20 years due to the growing demand for buildings, associated services and comfort levels. This increase comes with the people tendency to spend more time in buildings to which is added the continuous increase of the global population leading to higher energy consumption. As these underlying factors are not attenuating, energy efficiency in buildings represents a prime objective for energy policy at regional, national and international levels. Although people and organisation are often aware of the benefits of using energy more efficiently, a variety of social, cultural, and economic factors have precluded the adoption of energy efficient systems. As latest building equipments and control systems are transformed to be energy efficient, there are significant amount of savings that can be achieved [1–3]. With the continuous development, energy consumption in buildings is projected to rise substantially in the fastest-growing countries and especially in Europe. Such an increase of energy efficiency in buildings has three major objectives:

- a market assessment of the challenges, opportunities, and perceptions of energy efficiency in buildings;
- a thorough qualitative and quantitative evaluation of how to transform the building sector based on various market and regulatory mechanisms including codes and regulations, economical aspect, design and technology, skills upgrading and behaviour;
- commitment from the facility managers to do more to improve their energy use in their own buildings.

With the recent technological developments and knowledge as available today, dramatic reductions in building energy consumption can be achieved. In the new European Union regulations, there is a special directive for promoting energy performance in buildings, taking into account cost-effectiveness and local conditions and requirements (energy consumption in buildings is highly influenced by local climates and cultures).

In order to maintain a comfortable living/entertainment built environment, it is essential to meet multi-objective but often conflicting targets, e.g. minimum energy consumption, minimum CO2 emission, or maximum comfort level. Optimisation for building operation stage requires different methodologies/approaches compared to design stage, e.g. some key design variables are no longer available for changing (to find the most optimum solutions for design). It needs to take the as-built building environment to find the optimum solutions either against single or multi-objectives [4–6]. To provide practical real time decision making in building energy management according to the real time monitored data first the ‘behaviour’ of building energy systems by using various simulation tools must be understood. During the process, the iterative energy audition and involvement with end user/domain experts are needed in order to identify the main use cases and scenarios with associated input parameters and feasible outputs. It is therefore important to identify the required optimisation objectives which can be further confirmed via sensitivity analysis. Further, in the modelling process different relevant components have to be assessed and calibrated iteratively, and the developed building energy simulation model is then executed (as the calculation engine) within a generic optimisation program. For most of the existing simulation tools, e.g. EnergyPlus, TRNSYS, etc., the simulation process (for a comprehensive analysis) is normally very time consuming; and for an optimisation process, it normally needs tens/hundreds repeating simulation runs. An alternative solution is to speed up the ‘calculation engine’ for optimisation either by simplifying the simulation model or by utilising high power computing techniques. A preferred option is to use artificial intelligence instead such as neural network with heuristic learning algorithms applied on large amount of historical monitored data/simulated (manufactured) data sets.

In this paper we propose a modular optimisation system for deploying building optimisation by having as an objective the reduction of energy consumption in large scale building facilities. We develop the optimisation framework and provide a comparison analysis between: (i) modular optimisation system – where different objectives are achieved by the combination of three different optimisation modules and (ii) prediction based optimisation – where the actual optimisation process is undertaken by a artificial neural network (ANN). By deploying these optimisation modules on a high performance computing infrastructure we explore different scenarios as identified in a pilot sport facility. We demonstrate that our optimisation framework can deal with various input parameters and pre-determined optimisation objective and can greatly contribute to the overall process of enhancing energy efficiency in buildings.

The reminder of this paper is organised as follows: Sections 1–3 outline the development and use of optimisation systems, providing a key motivation for our research (and analysing several related approaches in this area). In Section 4 we present the computing infrastructure and applications supporting the optimisation framework. Section 5 presents the model explaining the methodological details of the optimisation. We validate the approach in Section 6 and present our conclusions in Section 7.

2. Previous studies

Energy optimisation in buildings has been widely investigated over the last few years. There are a number of researching attempts seeking to address energy efficiency in buildings [4–6] alongside with numerous researching projects that have been undertaken trying to identify best practises in the field of energy efficiency.

Cleanex [7] is a research project aiming to develop an innovative projectile based on-line cleaning and injection system that can work under the required operating conditions to mitigate foulant build-up throughout the heat exchanger. The proposed solution provides the industry with significant energy savings of over 10% and reduces the CO2 foot print across a wide range of industrial sectors [8]. NanoBAK [9] project approaches energy efficiency aspects in manufacturing industry. Bakeries are energy intensive, using large amounts of electricity and natural gas to operate the refrigeration system, compressed air system and ovens. Overall aim of the NanoBAK collaborative project is to facilitate efficient energy management in the baking industry and saves up to 50% of energy compared to conventional humidifiers. Thermonano [10] is another researching project aiming to develop nanofilled-polymer-based heat exchangers with the following objectives: (i) effective heat conductivity; (ii) cost reduction compared to metal materials and (iii) design flexibility for an intensive volume exploitation. Within the project, three main applications are devised such as (i) intercoolers increasing the efficiency of large diesel engines, (ii) heat recovery systems from combustion flue gases and (iii) application in the chemical and process industries. Enercom [11] project aims to demonstrate high-efficient polygeneration of electricity, heat, solid fuels and high-value compost/fertilisers from sewage sludge and greenery waste mixed to biomass residues. The project seeks to offer a new, safe, environmentally friendly and cost-effective path for the disposal of sewage sludge, maximising energy output. Setatwork [12] project

attempts to promote energy efficiency techniques in industry sectors connected with the carbon markets.

In current energy saving practises there are also a number of protocols for determining energy savings from energy efficiency measures and programs. These represent generally accepted standard methods that have been validated by technical experts in the field of energy program evaluation. International Performance Measurement and Verification Protocol (IPMVP) [13] is a standard defining terms and practises for quantifying the results of energy efficiency investments and increases investment in energy and water efficiency, demand management and renewable energy projects. IPMVP standard defines techniques for determining savings for facilities such as residential, commercial, institutional and industrial buildings. It also outlines procedures which can be applied to similar projects with varying levels of accuracy and cost, facilitating long-term energy savings. Another standard determining requirements and associated guidance for energy management systems is ISO 50001:2011. Created by the International Organization for Standardization (ISO) [14], the standard specifies the requirements for establishing, implementing, maintaining and improving an energy management system, enabling an organization to follow a systematic approach in achieving continual improvement of energy performance. The standard aims to guide organizations through the process of energy management and continually reduce their energy use, their energy costs and their greenhouse gas emissions. ASHRAE Guideline 14-2002 standard [15] seeks to provide adequate assurance for the payment of services by allowing for well-specified measurement methods for accurate saving calculations. It has also been adopted by governments to calculate pollution reductions from energy efficiency activities. As the guideline 14-2002 standard is more appropriate for individual buildings, or a few buildings served by a utility meter, large scale utility energy conservation aspects are not entirely addressed.

On the other hand, a number of different researching attempts have been developed around generic algorithms (GAs) and their efficiency in solving energy optimisation problems. However genetic algorithms do not guarantee optimal solutions, but they can produce high quality solutions in a reasonable amount time [16]. A disadvantage of GAs is that they require a large number of, sometimes thousands of, evaluations to find adequate solutions for complex optimisation problems [5]. Sefrioui et al. [17] developed a Hierarchical Genetic Algorithms (HGAs) with multi-layered hierarchical topology and multiple models for optimisation problems. The result was composed by a mix of simple and complex models with a significant improvement in regard to the processing time when compared with the complex models. For the problem of synchronism for migration of various parallel distributed GAs, Alba and Troya (2001) [18] extended the existing results to structured-population GAs and demonstrated linear and even super-linear speedup when run in a cluster of workstations. From the application perspective, Jelasity et al. [19] proposed a tool for automatic learning of algorithm components based on distributed evolutionary algorithms mapped on problem classes. The tool was based on a conceptual framework of multi-agent systems implemented in Java and capable of running distributed experiments on the Internet [20,21].

Although these solutions provide an alternative for reducing energy consumption, these efforts still leave undetermined how the system can cope with different scales of buildings where the complexity of the optimisation increases. In this work, we target to explore how a generic optimisation system can be applied to improve the efficiency of large scale buildings by exploring the performances of the system in real use case scenarios.

3. Approach

Energy efficiency practises include passive design strategies which generally focus on building shape and orientation, passive solar design, and the use of natural lighting. To improve energy efficiency and enable more active energy monitoring of buildings, energy management systems have been developed to provide advanced controls such as motion sensors and other wireless sensors that allow more detailed monitoring to be carried out with a higher frequency of data capture. Such energy systems also enable an automatic and instant distribution of receiver-tailored and pre-processed information (raw data, consumption trends, deviation alarms, etc.). They can perform triggered measurement and record of electricity, water, or gas consumption at different levels within a built environment/facility (sub-metering) and allow for remote access to the consumption data (e.g. using Power Line, GSM, or standard wired communication protocols). In such systems, it is also possible to dynamically alter the rate at which data capture takes place.

As the time associated with carrying out the energy optimisation process represents a key aspect, facility managers (i.e. those responsible for managing the built environment) aim to minimise

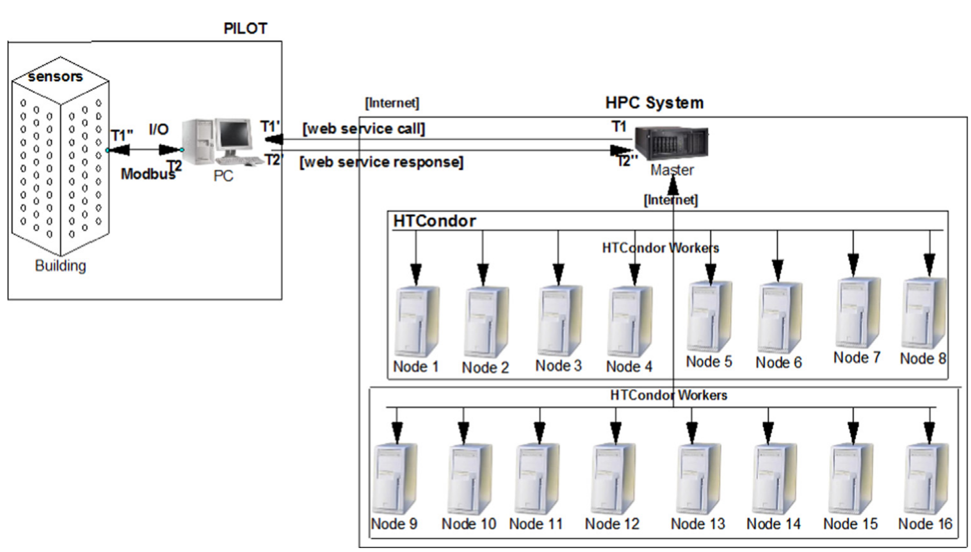

Fig. 1. Optimisation workflow and framework.

time and generate optimised set-points (identifying particular control objectives that need to be met by the facility managers). The time parameter is also important in real-time optimisation where delays can bring additional costs for the facility managers especially when building related parameters (such as temperature and occupancy) are frequently changing. The complexity of this process increases depending on the size of the facility involved – such as a sports' facility considered in this paper. With the increase of performance of control systems and sensors, facility managers are more and more interested to implement and adopt optimisation strategies (see Fig. 1). Such facility managers are interested in running the optimisation process and to obtain the required results in a limited time period and implement the optimised set-point adequately in the building. In practice, such an optimisation process will require multiple executions of an optimisation package, such as EnergyPlus, with different parameter ranges to which an GA based optimisation or ANN prediction can be applied. We consider two key parameters here: (i) *complexity of the building model* has a direct impact on the overall simulation time; (ii) *simulation period*, i.e. the time interval over which the energy optimisation is carried out – can range from 1 week to 1 year, for instance.

Similarly, the optimisation system must comply with two parameters:

- *Time-to-complete*: An optimisation plan needs to be completed by a particular time deadline. Assuming that monitoring systems can deliver readings every 15 min, the optimisation process also needs to be carried out over an equivalent period. Each new execution uses as an input the last configuration of the building and set points (for various control outputs) associated with the building.
- *Results quality*: An optimisation process, as identified in this study, consists of a number of steps that can be undertaken via multiple EnergyPlus runs, ANN based process of GA based optimisation. Depending on the complexity of the building and the period to optimise, a time interval is associated with each optimisation process. If suitable computational resources are not available, it may become necessary to sacrifice the quality of results and complete only a part of the required rounds of optimisation in order to comply with the time deadline. Returning a partial optimisation result may have a two-fold impact: (i) reduces the number of resources needed to carry out the simulation/optimisation; (ii) influences the accuracy of the energy optimisation plan undertaken by facility managers.

For instance, if the optimisation process provides lower quality results, the overall efficiency of the energy consumption plan can decay leading to an increase of cost.

4. Computing infrastructures and applications

We deploy our optimisation system on a cluster based infrastructure with 12 dedicated cluster machines. Each machine has 12 CPU cores and 3.2 GHz CPU speed. Each physical machine uses a KVM (Kernel-based Virtual Machine) virtualization environment with each entity (master, workers, request-handler) within our system, occupying a single virtual machine. Each virtual machine runs Ubuntu Linux utilising one 3.2 GHz core with 1 GB of RAM and 10 GB storage capacity. In our system masters and slaves are running on a separate machines and using the capability of the machines for their corresponding roles as follows: (i) slaves are in charge of computing the actual tasks received from the users and (ii) the master generates tasks based on the users' requests, submits tasks into the space and collects results (see Fig. 1).

4.1. HTCondor

HTCondor is an open-source high throughput computing workload management software framework for a cluster of distributed computer resources. As most of the personal computers have more processing power and storage space than the supercomputer of last century it has become possible to build a network of computers. HTCondor is widely used to utilise the distributed computers to their full potential for computational intensive tasks, such as simulation calculations [22]. The mechanism of task scheduling in HTCondor is different to the mechanism of related systems. In HTCondor system, after the submission, the jobs run until a user tries to use the computer interrupting the processed job and then restart it on another available machine. HTCondor can be used to manage a cluster of dedicated compute nodes (our case) greatly enhancing the completion time and balancing the load. In our case, the machines are part of a dedicated cluster and every task submitted to HTCondor will be processed without interruption. HTCondor has two components: job and resource management. Job here is defined as a process, or set of processes, executed on the condor pool. The job management component is responsible for handling the job execution allowing users to query the job queueing and execute a new job. The resource management component specifies policies for scheduling, priority scheming and resource monitoring. With the efficacious mechanisms such as task scheduling and multi-task parallel processing, HTCondor based system can greatly facilitate the acceleration of task processing. HTCondor also provides a high level of fault tolerance, functioning with crashes, network outages or any single point of failure that might appear [23].

In this study we use HTCondor to deploy energy optimisation processes. To demonstrate our approach we have evaluated real scenarios, which illustrate the feasibility and effectiveness of our approach.

4.2. Energy plus

EnergyPlus has been validated as a efficacious tool for running energy simulations [24]. EnergyPlus is an energy analysis and thermal load simulation tool for allowing building performance simulations such as lighting/daylighting, HVAC, service water heating, and on-site energy generations. Based on a user description of a building, EnergyPlus can calculate the heating and cooling loads necessary to maintain thermal control setpoints, conditions throughout a secondary HVAC system and coil loads, and the energy consumption of primary plant equipment. In EnergyPlus, inputs and outputs are accomplished by means of ASCII (text) files. On the input side, there are three files:

- The input data dictionary (IDD) that describes the types (classes) of input objects and the data associated with each object.
- The input data file (IDF) that contains all the data for a particular simulation.
- The weather data file (EPW) that contains all the data for exterior climate of a building.

In addition, EnergyPlus can be used as an energy simulation engine employing a simultaneous load/system/plant simulation methodology. In load calculation, different methods are used to calculate heat conduction through envelopes and then a heat balance method for zone load [25,26]. Moreover, EnergyPlus makes use of a modular, loop-based method to simulate HVAC

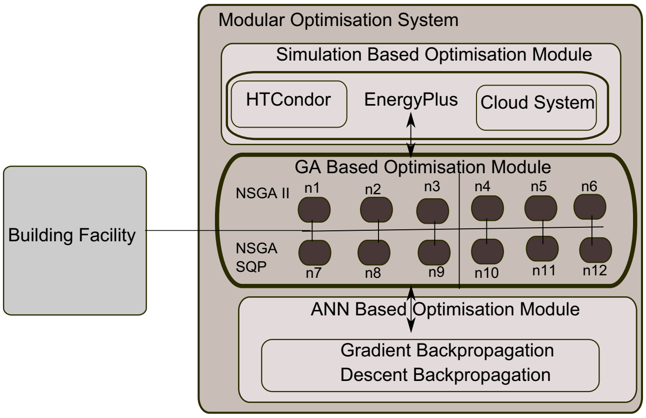

Fig. 2. Optimisation modules.

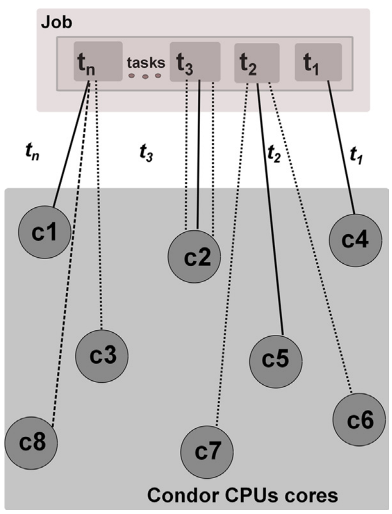

Fig. 3. Optimisation modules.

systems which help accelerate the model construction process [27]. Through the object of "Setpoint Manager" in EnergyPlus, many different kinds of variables such as supply air temperature and chilled water supply temperature can be controlled and this function facilitates the construction of modern advanced supervisory control.

From a computational perspective EnergyPlus necessitates reliable computational infrastructure to run. When dealing with small EnergyPlus models (with a small number of surfaces, zones, and systems), which do not require a large amount of computer memories, PCs with faster CPUs are more effective in reducing run time than PCs with more memory. For large models, more and faster computer memory including RAM and internal cache may be more effective in reducing run time. If an energy model simulation produces hourly or time step reports, the hard drive access speed also becomes important in reducing run time.

5. Optimisation framework

An optimisation process is mapped as a job defined as $job: f(input, obj, deadline)$, where *input* identifies the input data represented as $input$:$f(IDF, W, [param])$, *IDF* represents the building model to be simulated, *W* represents the weather file required for the simulation, $[param]$ defines a set of parameter ranges associated with the *IDF* file $[param] = (x_m, x_n)$. The objective of a job *obj* represents the objective of the optimisation process $obj: f(outVarName, min/max)$, defining the name of the output variable to be optimised *outVarName* and the target of the optimisation process *min/max*, where min specifies the minimisation the *outVarName* and max defines the maximisation the *outVarName*. The parameter *deadline* defines the time interval associated with the job:

$$f(input, obj, deadline): \begin{cases} input: f(IDF, W, param); \\ obj: f(outVarName, min/max); \\ deadline: f(t). \end{cases} \quad (1)$$

A job contains a set of tasks $N = \{t_1, t_2, t_3, \ldots, t_n\}$ to execute within the computing environment. Each task t_{si} is characterised by two parameters $t_i \rightarrow [ID, data]$ where *ID* is the ID of the task, *data* represents one set of values generated from the combination of the parameter ranges defining the job: $[data]: f([parameters])$, $[data] = \{p_1, p_2, p_3, \ldots, p_n\}$, where $p_i \in (x_m, x_n)$.

As illustrated in Fig. 2, the optimisation framework consists in three separate modules deployed on a high computing infrastructure. After definition, an optimisation process (mapped as a job) is processed within the following modules: (i) simulation based optimisation module, (ii) ANN optimisation module and (iii) GA optimisation module.

5.1. Simulation based optimisation module

The simulation based optimisation module undertakes real-time simulation based optimisation processes based on the HTCondor system by executing EnergyPlus simulation instances. A simulation based optimisation process is a function $f(s): I_s \rightarrow R_s$, where the set I_s identifies the input parameters and associated values as recorded by sensors in the building, and R_s is a set identifying the results of the simulation based optimisation.

The HTCondor model is designed to be dynamically updated, where each worker communicates with others, discovers available resources, and determines capabilities. In HTCondor, tasks are launched in parallel which increases the fault tolerance of the overall process (see Fig. 3). Another key benefit of this execution environment is the possibility to schedule tasks and take advantage of available capabilities on registered workers. The deployed HTCondor pool has two different execution strategies in operation: (1) the traditional approach where Condor only deploys jobs on idle machines, and (2) an approach where HTCondor deploys jobs onto machines regardless of whether they are idle or not. However, HTCondor processes on these machines are given the low thread priority, allowing them to only make use of spare CPU cycles. We have adopted the approach where tasks are always submitted, for the obvious advantage that we had dedicated machines, hence the number of available nodes remains constant and there is a low rate of machine failure. To simplify the Condor submission process we have updated some functionality on workers so that they advertise their ability to run EnergyPlus simulations. We have furthermore addressed variations in machine availability by extending the HTCondor scheduling mechanism for allowing the scheduler to submit jobs whether a machine is idle or not. Despite this the approach does not have a significant effect on the machine, as for the most part jobs go unnoticed.

5.2. Artificial neural network based optimisation module

The ANN based optimisation module can function independently for solving an optimisation process or can be embedded within the GA based optimisation module. We map an ANN based optimisation process as a function $f(a): I_a \rightarrow R_a$, where I_a is a set representing the input of the ANN optimisation and R_a is a set identifying the results of the ANN optimisation. It is important to

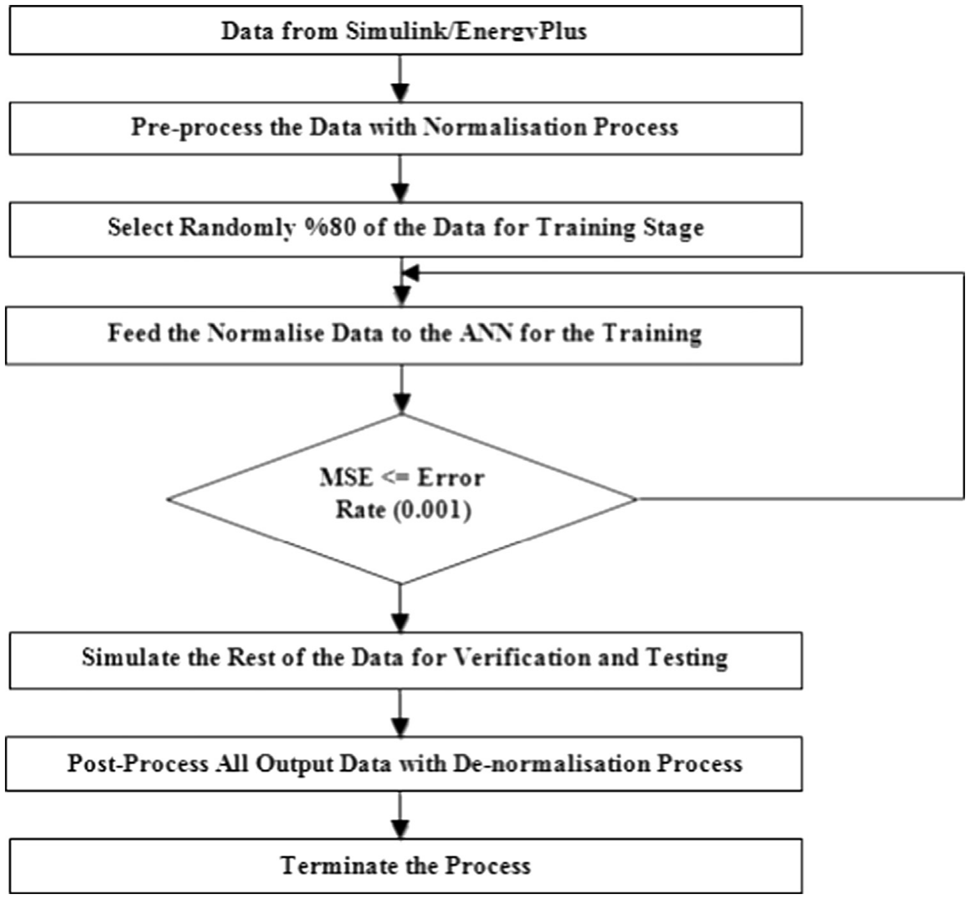

Fig. 4. ANN process workflow.

note that the input set I_a can be formed by historical data of parameter values recorded in the building facility over time or can be obtained from the results of the simulation based optimisation such as $I_a = R_s$. With the large amount of training, the ANN module can replace the simulation module and provide an optimised result in a shorter time interval. We use a calibrated simulation model to generate a large amount of data sets to train the corresponding ANN prediction engine. The trained ANN was then calibrated in real case and used as a cost function in an optimization program to help us to achieve energy saving target (see Fig. 4).

Several ANN models have been tested to find the best configuration on both Visual Studio platform and MATLAB. For C++ Based Fast ANN (FANN) models we have used: (i) standard backpropagation – where the weights are updated after each training pattern and (ii) Advanced batch training – not use the learning rate (default training algorithm). For MATLAB based ANN Models we have used: (i) conjugate gradient backpropagation with Powell–Beale restarts and (ii) gradient descent backpropagation (Fig. 5).

During the training process 80% of the data sets has been randomly selected and used. The rest of the data sets was utilised for the testing stage. The data sets used in this process are selected from facility scheduled opening hours.

5.3. Genetic algorithms based optimisation module

For our GA based optimisation module we use a number of generic algorithms such as (i) NSGA, (ii) NSGA II and (iii) SQP. The GA based optimisation module can work independently or in combination with the ANN optimisation module and the simulation based optimisation module. We consider a GA based optimisation as a function $f(g): I_g \rightarrow R_g$, where I_g is a set defining the input parameters of the GA based optimisation and R_g is the resulting set of the GA based optimisation. The I_g input set of the GA optimisation can identify: (i) historical data of parameter values recorded in the building facility over time, (ii) results of the simulation based optimisation such as $I_g = R_s$ or (iii) results of the ANN based optimisation such as $I_g = R_a$. As part of the GA based optimisation module, NSGA-II is a non-domination based multi-objective genetic algorithm. It begins with randomly selected individuals which are called a generation. These individuals are classed into two populations according to their ranks of fitness. The best solutions are selected to create a new offspring population by applying genetic operations. The current generation and current offspring are sorted again based on non-domination and crowding distance. The best individuals are selected to form the next generation of the process.

The parallel NSGA-II, presented in this paper, is a global single population master–slave synchronous parallel genetic algorithm. As shown in Fig. 6, firstly, the parallel NSGA-II algorithm initialises its parameters, such as population size, crossover probability, mutation probability then it triggers the optimisation iteration process. A set of random individuals is selected which are grouped and called as “a generation”. Each individual represents a point in the searching space of the optimisation model. The coordination of a point is one configuration of the building simulation model. Accordingly, a HTCondor job is created for each individual of the population. The job contains a submit job file, a simulation input data file, a job working folder, and other necessary files for building simulation software. After these jobs are submitted to the HTCondor computation environment, the algorithm waits for the jobs to finish. When all the jobs are completed, the algorithm collects objectives and constraints from the output files of the simulation. If the optimisation terminating condition is met, the optimisation iteration finishes. Alternatively, it triggers the next optimisation iteration.

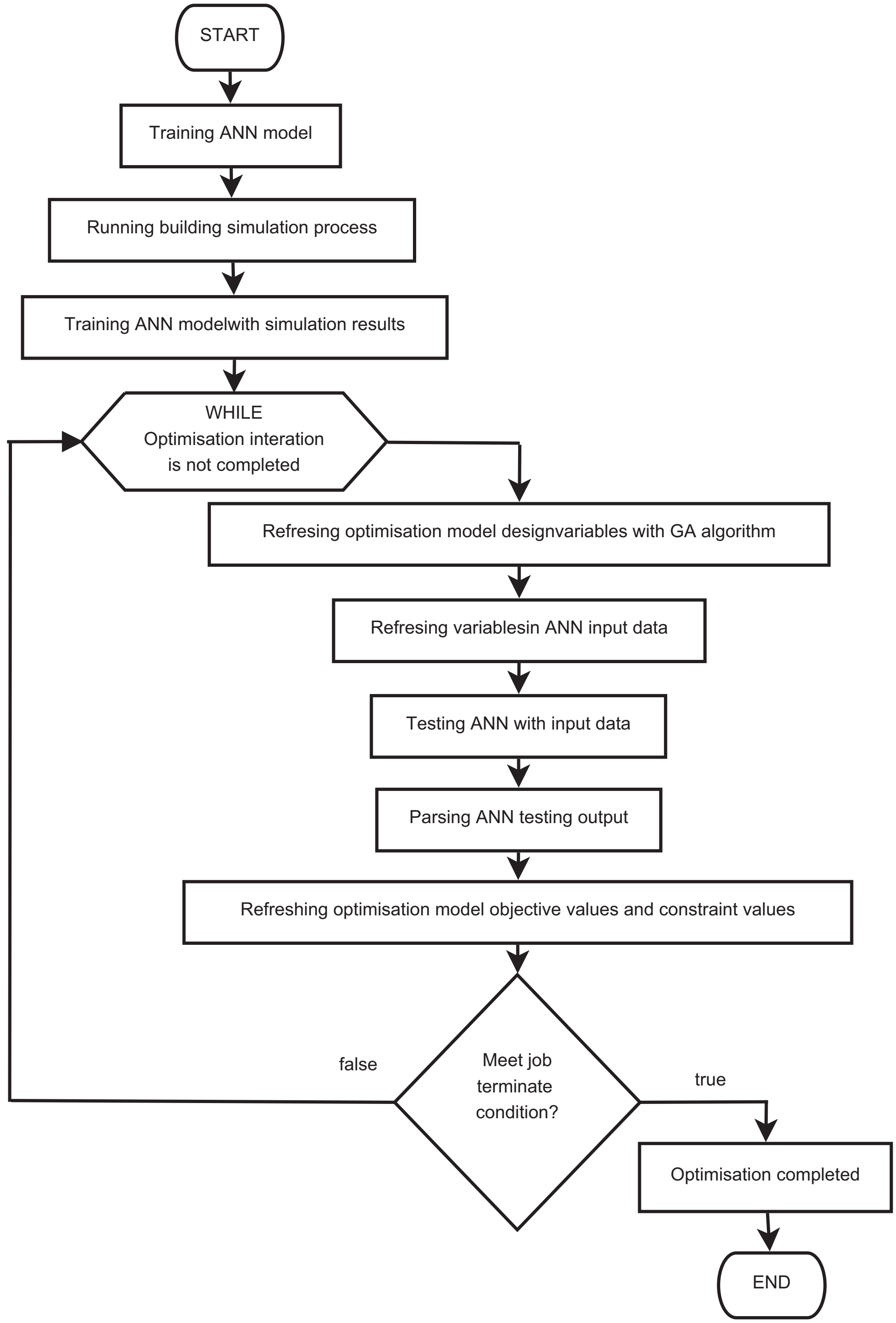

Fig. 5. ANN based optimisation.

On the other hand, sequential quadratic programming (SQP) method is used when looking for an optimum solution in a shorter time interval. SQP is one of the most utilised methods for numerical solutions of constrained non-linear optimisation problems:

$$f(n) = \begin{cases} \min & Q(x) = \frac{1}{2}x^T Gx + g^T x \\ \text{s.t.} & a_i^T x = b_i, \quad i = \{1, 2, 3, \ldots, m\} \\ & a_i^T x \le b_i, \quad i = \{m, m+1, \ldots, p\} \end{cases} \tag{2}$$

The basic idea of SQP is to model the targeted optimisation model at a given approximate solution x_k, by a quadratic programming sub-problem. Then the solution to this sub-problem is utilised to construct a better approximate solution, x_{k+1}. This iterated process creates a sequence of approximations which will converge to a solution, $x*$, for the targeted problem. The fast converging speed of SQP method mainly comes from the rapid and accurate procedures for solving quadratic optimisation problems.

6. Evaluation

We validate the presented approach by testing its efficiency in a real world scenario. We deploy the modular optimisation on our

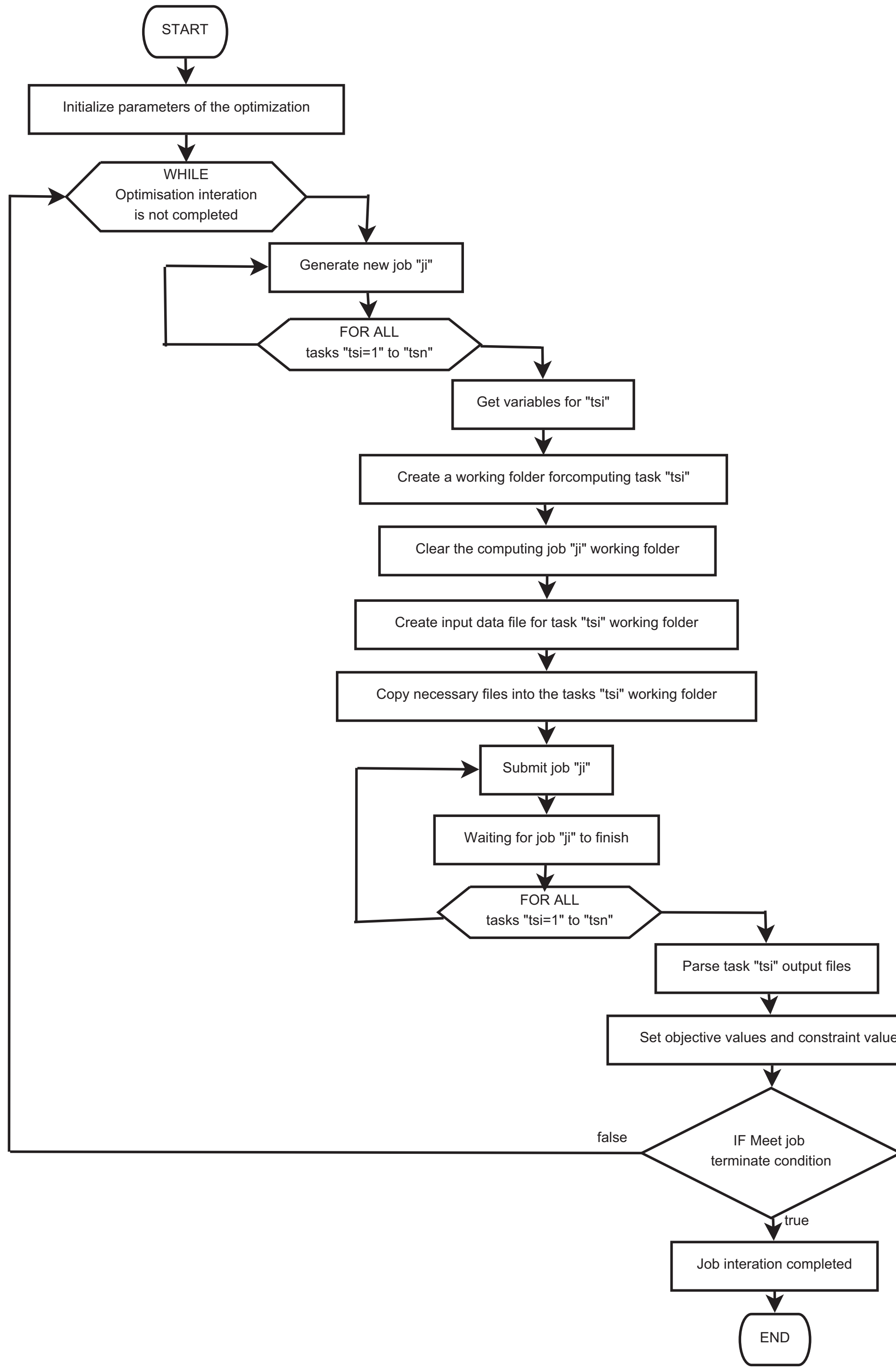

Fig. 6. Algorithm for parallel processing on HTCondor.

computing infrastructure and record the results for a monitored period of 42 days. For undertaking these experiments and providing a comparison base, we use one of the *SportE*^{2}[1] pilots called FIDIA,[2] a public sport building facility, located in Rome, Italy (see Fig. 7).

6.1. FIDIA pilot

The building we have used in the pilot study has wooden external walls of 9 cm and a wooden external roof of 9 cm. The

[1] *SportE*^{2} is a research project co-financed by the European Commission in FP7 under the domain of Information Communication Technologies and Energy Efficient Buildings. In this project, we develop energy efficient products and services dedicated to needs and unique characteristics of sport facilities, www.sporte2.eu.

[2] http://www.asfidia.it

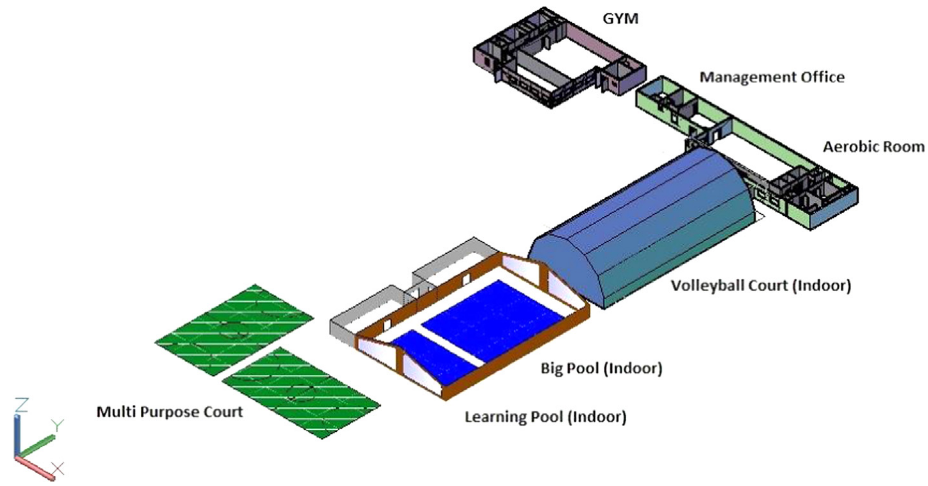

Fig. 7. FIDIA pilot representation.

floor is made of concrete. The windows are single glass with a thermal transmittance of 5.7 W/m^2 K and a solar gain of 0.7. The geometry of the building is composed of a Gable roof with Hmin = 3 m and Hmax = 6 m with window surfaces of about 70 m^2. In addition the building pilot is structured as follows:

- Pool (indoor) – size: 25 m × 16 m, depth: 1.60–2.10 m, capacity: 760 m^3.
- Learning pool (indoor) – size: 16 m × 4 m, depth: 1 m, capacity: 64 m^3.
- 1 Gym (indoor) provided of electric equipment (electric bicycles, etc.).
- 1 Fitness room (indoor) size: 18 m × 9 m × 3 m, volume: 486 m^3.
- 1 Volleyball court (indoor) – size: 40 m × 28 m × 8 m, volume: 8960 m^3.
- 2 Tennis/five-a-side courts (outdoor, with changing rooms) – size: 30 m × 20 m.

The sports' facility is equipped with sensors and actuators for monitoring, control and optimisation of the facility. The building has metering capability to determine consumption of electricity, gas, biomass, water and thermal energy. This data can be accessed through a specialist interface and recorded for analysis: the sub-metering of thermal and electrical consumption within grouped zones (gym/fitness and swimming pool are also provided along with "comfort" monitoring by functional area: gym, fitness room and swimming pool). In these areas the Predicted Mean Vote (PMV) index (which measures the average response of a group of people to a thermal sensation scale – such as hot, warm to cool and cold) – is one of the most widely recognised thermal comfort models, and is measured as a function of the activity performed within a particular part of the building. The occupancy is also monitored in the gym, fitness room and around the swimming pool area. The structure of the facility does not allow the direct measurement of the total value of occupancy for the pilot, so the occupancy of the whole facility is provided as a sum of the number of people who have entered/exited the building over a particular time interval.

6.2. Configuration

In our FIDIA pilot optimisation we have used the following setup.

Objectives: The objective of this scenario is to reduce energy consumption while maintaining indoor thermal comfort. FIDIA HVAC energy consumption consists of two components: thermal energy and electricity consumption, therefore energy consumption function can be described as follows: $E = E_t + E_e$, where E_t and E_e represent thermal energy consumption and electricity consumption respectively. E represents the total energy consumed by the building facility over the monitored period.

Constraints: *PMV* is used as one constraint for the optimisation model. As mentioned previously, the acceptable comfort zone is defined as $-1 < PMV < +1$ in this scenario.

Variables: The input parameters and output results are presented in Table 1.

Thus, we evaluate the impact of our optimisation solution from the perspective how much energy can the pilot (FIDIA) save over a period of time. We have recorded the "real energy consumption" as identified in the FIDIA pilot over a period of approximately 42 days and compared with the results obtained when running the optimisation within our modular optimisation methodology. It must be noted that the optimisation process was conducted based on the real input data recorded from the pilot to which we have applied an Energy Plus optimisation process deployed on our computing infrastructure.

In our evaluation cases we compare the modular optimisation, as identified in this paper, with traditional optimisation techniques as existing in the pilot. A traditional optimisation technique refers to a number of operations that pilot personnel are adopting for reducing energy. All these operations are manually applied (i.e. switching off the boiler, the air fans, the lighting system, etc.) and have no automated implementation or consistent decision making process. An modular optimisation, on the other hand, is based on a number of modular techniques (see Section 5) and is related to a set of input parameters and generates optimised values according to which setpoints within the building are automatically adjusted. For providing a better comparison base to our experiments we have included an additional predicted trend for the variables that we monitored. The predicted mechanism is ensured by employing an artificial neural network which works independently. The ANN used for prediction has been developed based on the methodology presented in Section 5.2.

Values of the reported variables have been recorded at intervals of 15 min for a period of 42 days. We consider a set $R : \{r_1, r_2, r_3, \ldots, r_n\}$, where r_i represents a generic value recorded at every 15 min for thermal energy consumption (TEC), electricity consumption (EEC) and PMV. We have used three different methodologies for representing the results:

- Interval records – r_i, identifies the distribution of the reported metrics as recorded every at 15 min intervals (Case 1).
- Day average records – $average=(1/n)\sum_{i=1}^{n}(r_i)$ (Case 2, Case 3 and Case 4).
- Total per day records – $total=\sum_{j=1}^{m}(r_j)$ (Case 3, Case 4 and Case 5).

6.3. Results

Case 1: Day energy consumption: modular optimisation vs. traditional optimisation method.

This experiment is illustrated in Fig. 8 and shows how energy consumption evolves in FIDIA over a monitored period of 1 day (24 h): (i) consumption with traditional optimisation and (ii) consumption with modular optimisation. It can be observed that the energy consumption, as recorded in the pilot and undertaken with traditional optimisation methods, fluctuates between 0 and 100 kWh with a peak value of 300 kWh. For the modular based optimisation, the energy consumption fluctuates over the interval of 0–38 kWh. We can immediately conclude that modular optimisation imposes a uniformity over the energy consumption.

From Fig. 8, we can also identify two consumption schedules: (i) day schedule ([0–20] recording stages and [50–100] recording stages) and (ii) night schedules ([20–50] recording stages). Whereas during the day schedule the energy consumption is high, over night the consumption is minimum. However, as traditional optimisation techniques have no intelligent decision making process, for some night intervals energy consumption is still high. Modular optimisation assumes a continuous adaptation based on the values read from sensors in intervals of 15 min. This process of continuous adaptation associated with an intelligent optimisation mechanism facilitates significant energy savings. For the monitor period of 1 day, the savings in terms of energy consumption obtained by using modular optimisation are of 412.20 kWh equivalent with a saving percentage of approximately 39%.

Case 2: Day average energy consumption and PMV.

In this experiment we represent how the day average of total energy consumption (thermal energy and electricity) evolves with PMV over the monitored interval of 42 days.

As illustrated in Fig. 9, the relationship between energy consumption and PMV is a direct. It must be noted that our modular optimisation tries to reduce energy consumption while keeping an optimum comfort within the facility. It can be also observed that an additional consumption of energy impacts the PMV by increasing its level. This happens because our modular optimisation model (see Fig. 1) uses as an input a number of building parameters such as occupancy, indoor and humidity, and associates a degree of importance to PMV in regard to the other two objectives – thermal energy consumption and electricity consumption.

Table 1
Optimisation input and output.

Input and outputs	Unit
Optimization inputs	
Occupancy	–
Indoor temperature	°C
Water temperature	°C
Indoor temperature	%
Supplied air flow rate	Kg/s
Day	–
Month	–
Year	–
Inlet air temperature	°C
Optimization outputs	
Optimized set point for inlet consumption	°C
PMV	–
Optimized electrical energy consumption	kWh
Optimized thermal energy consumption	kWh

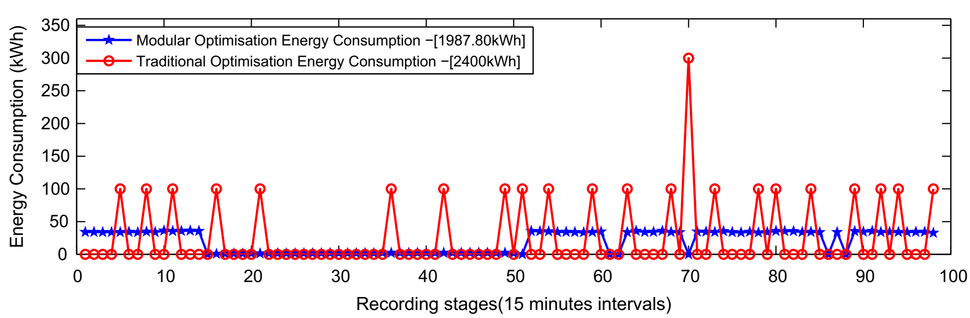

Fig. 8. Thermal energy consumption: modular optimisation vs. traditional optimisation method.

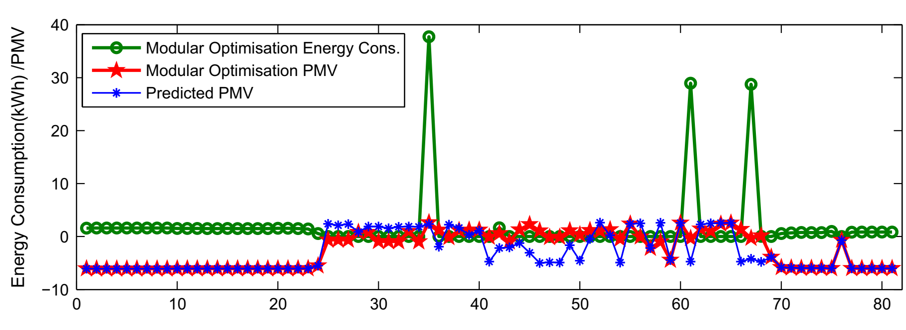

Fig. 9. Total energy consumption and PMV.

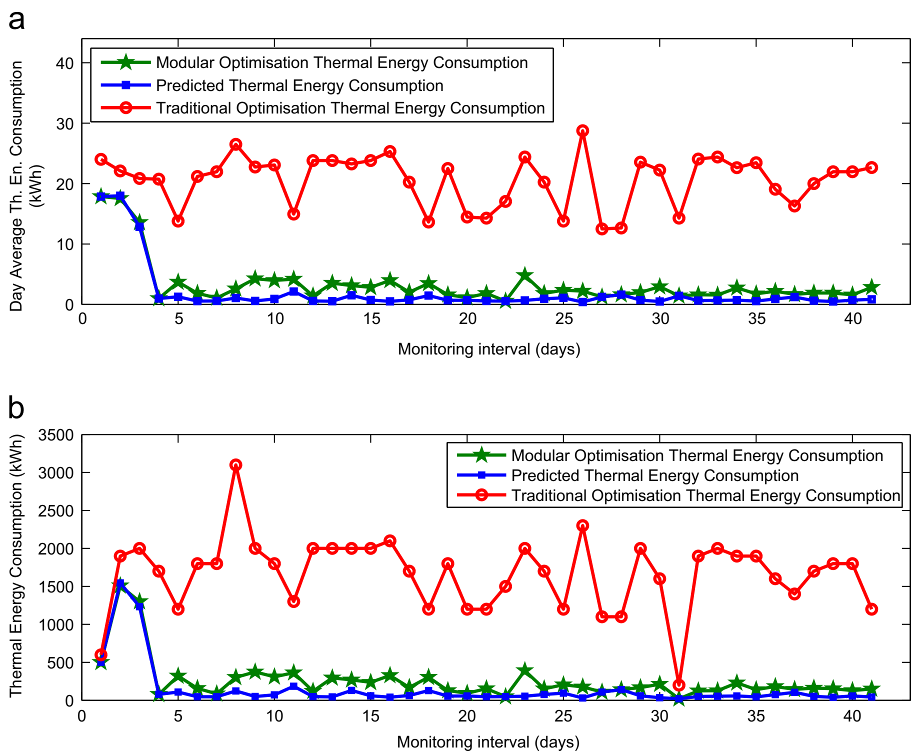

Fig. 10. Thermal energy consumption: modular optimisation vs. traditional optimisation method. (a) Day average thermal energy consumption. (b) Total thermal energy consumption.

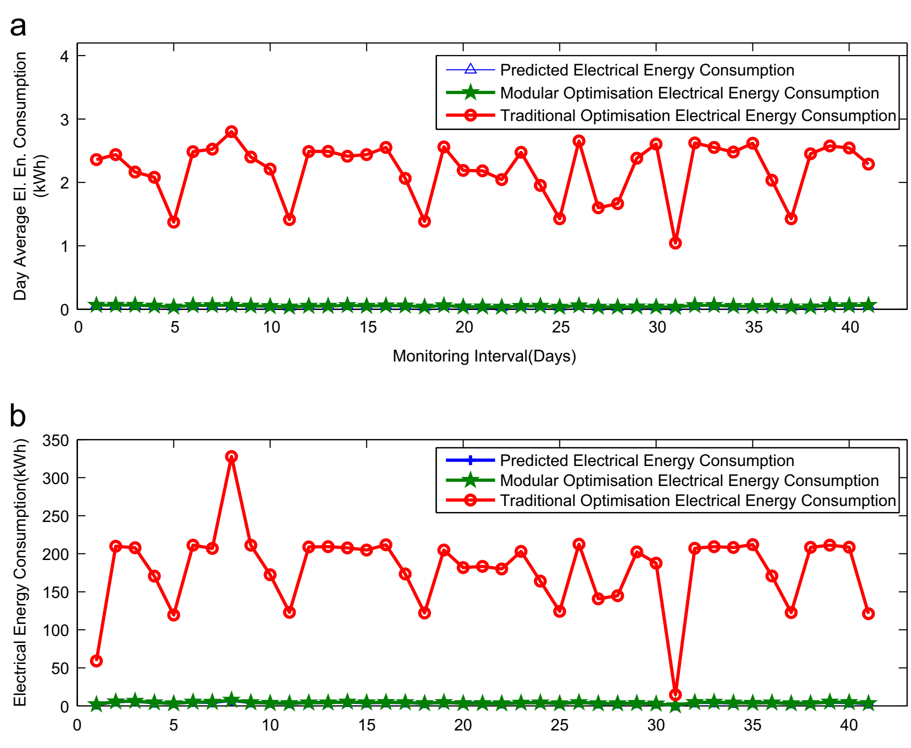

Fig. 11. Electrical energy consumption: modular optimisation vs. traditional optimisation method. (a) Day average electrical energy consumption. (b) Total electrical energy consumption.

Case 3: Thermal energy consumption: modular optimisation vs. traditional optimisation method. In this case we are interested to show how thermal energy consumption (TEC) evolves within the two scenarios that we compare (i) modular optimisation and (ii) traditional optimisation. For a better comparison base we have used an additional artificial neuronal network to predict energy consumption.

From Fig. 10 it can be identified that our modular optimisation model facilitates significant energy savings. It is important to note that this experiment illustrates the total thermal energy

Table 2
Summary of savings of energy consumption.

Monitored period	Saved energy (kWh)
One day	412.20
One week	6026.99
Two weeks	14 842.14
One month	32 969.66

consumption per day over the monitored interval of 42 days. As illustrated, the thermal energy consumption with traditional optimisation is high, varying over the interval of 500–3100 kWh with an average per day of 1665.85 kWh. On the other hand, the optimised thermal energy consumption evolves within the interval 50–1500 kWh with an average per day of 257.77 kWh. This process of continuous adaptation associated with an intelligent modular optimisation mechanism facilitates significant energy savings at every 15 min intervals the modular optimisation reacts according to the latest changes within the building.

Case 4: Electrical energy consumption: modular optimisation vs. traditional optimisation method.

In this experiment we are interested to show which is the impact of our modular optimisation system on the electricity consumption (EEC). It is important to note that in FIDIA pilot the electricity consumption is at minimum as it is only used to heat the air in the fans.

From Fig. 11 it can be observed how electricity consumption evolves within the two cases that we analyse. Whereas for traditional optimisation the consumption is high fluctuating over the interval of 59–330 kWh with an average of 180 kWh per day, when using our modular optimisation system the consumption drops to an average of 4.04 kWh per day. Thus, we demonstrate again that modular optimisation undertaken with a frequency interval of 15 min can greatly contribute to also reducing electricity consumption.

Case 5: Total energy consumption over monitored periods: modular optimisation vs. traditional optimisation method.

We have varied the monitored period to intervals of 1 week, 2 weeks and 1 month and investigated how our modular optimisation system performs. We have noticed that the positive results identified for a monitored interval of 24 h are also applicable for different intervals.

Table 2 presents a summary of the total energy consumption over different monitored periods when the two optimisation techniques (modular based optimisation and traditional optimisation) are used. Significant differences can be noted between the two optimisation approaches with corresponding fluctuation intervals of 0–100 kWh for traditional optimisation and 0–38 kWh for modular based optimisation. The results are encouraging and show that our approach can dramatically reduce the energy consumption of a building. However, it must be noted that this result is very much related to the properties of the building and to the period of the year when data are collected and optimisation applied.

7. Conclusions

We present our optimisation system by introducing three interactive modules that can greatly facilitate the generation of optimal set-points within a building. We have presented the design and implementation of the proposed approach and experimentally evaluated a number of scenarios emphasising the savings in terms of thermal energy and electricity consumption. From the results, we can conclude that the modular optimisation provides a number of advantages regarding to energy savings such as uniformity over consumption intervals, balance between optimisation objectives and greatly assisting building managers to employ efficient decisions.

We demonstrate that our modular optimisation can represent a reliable solution not only for complex energy optimisation problems but can be easily extended to other type of problems. We validate our optimisation module by using a comparison based approach with real data recorded from one of the project pilots called FIDIA, a sport facility in Rome, Italy. The advantages of our solution rely not only on the performances of the HTCondor system but also on the unique combination of different modules such as simulation module, optimisation algorithms' module and artificial neuronal network module. By combining these environments within a single solution we facilitate an optimum between the optimisation objectives, energy savings and corresponding costs.

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